Long-Short-Term Memory Model for Fake News Detection in Nigeria

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Abstract

Background: The advent of technology allows information to be passed through the Internet at a breakneck speed and enables the involvement of many individuals in the use of different social media platforms. Propagation of fake news through the Internet has become rampant due to digitalisation, and the spread of fake news can cause irreparable damage to the victims. The conventional approach to fake news detection is time-consuming, hence introducing fake news detection systems. Existing fake news detection systems have yielded low accuracy and are unsuitable in Nigeria.

Objective: This research aims to design and implement a framework for fake news detection using the Long-Short Term Memory (LSTM) model.

Methodology: The dataset for the model was obtained from Nigerian dailies and Kaggle and pre-processed by removing punctuation marks and stop words, stemming, tokenisation and one hot representation. Feature extraction was done on the datasets to remove outliers. The locally acquired dataset from Nigeria was balanced using Synthetic Minority Oversampling Techniques (SMOTE) Long-Short Term Memory (LSTM), a variant of Recurrent Neural Network (RNN)- which solved the problem of losing gained knowledge and information over a long period faced by RNN- was used as the detection model This model was implemented using Python 3.9. The model detected fake news by classifying real and fake news approaches. The dataset was fed into the model, and the model classified them as either fake or real news by processing the dataset through input and hidden layers of varying numbers of neurons. accuracy F1 score and detection time were used as the evaluation metrics. The results were then compared to some selected machine learning models and a hybrid of convolutional neural networks and long short-term memory models (CNN-LSTM).

Results: The result shows that the LSTM model on a balanced dataset performed best as the two news classes were accurately classified, giving an average detection accuracy of 92.86%, which took the model 0.42 seconds to detect whether news was real or fake. Also, 87.50% average detection accuracy was obtained from an imbalanced dataset. Compared to other machine learning models, SVM and CNN-LSTM gave 81.25% accuracy for imbalanced datasets and 82.14% and 78.57% for balanced datasets, respectively.

Conclusion: The outcome of this research shows that the deep learning approach outperformed some machine learning models for fake news detection in terms of performance accuracy.

Unique contribution: This work has contributed knowledge by employing an LSTM model for detecting Nigerian fake news using an indigenous dataset.

Key Recommendation: Future research should increase the data size of indigenous datasets for fake news detection to achieve improved accuracy.

Keywords: Fake news, SMOTE, accuracy, detection, model, deep learning

Introduction

Recently, technology has found its way into the lives of individuals, government agencies and the private sector, and this digitisation has accelerated the spread of information dissemination around the globe as there is no hidden information any more (Georgiadou, 1995). The advent of technology has turned the whole world into a global village, allowing information to move from a source to the viewer at a breakneck speed through the internet, but when this disseminated information is not verifiably accurate, it consequently causes misinformation, disinformation and mal information called fake news. In addition, the current pace of digitalisation with respect to technological advancement has brought about the rapid involvement of every individual in different social media platforms. This gave the people a level of independence and an extreme level of freedom of expression and opinion, which is actually a great advantage as it leaves no room for intimidation or fear (Ezema & Inyama, 2012).

Fake news can be described as claims or stories that are purposefully and verifiably untrue and attempt to pass themself off as news or journalistic reports (Kaplan & Haenlein, 2010). It can be challenging for average people to distinguish this type of news from the plethora of information publicly available because of restrictions in knowledge and experience. Fake news is often spread by yellow journalism with the intention of glorious news like hilarious news, accidents, rumours, and crime news (Islam et al., 2020). In this digital era, it is easier to spread fake news because a user may distribute fake news to neighbours, family and friends through social media (Habib et al., 2019). Villafranca and Peters (2019) recent study shows that the dispersion of fake news on social media platforms propagates six times faster than the truth. Hence, there is a need to apply artificial intelligence for fake news detection.

Fake news detection is a method of classifying real information from rumours that might lead to a political uprising and disunity in society Sharma et al. (2020). Several approaches, ranging from traditional machine learning to deep learning, have been employed by various researchers to detect fake news. Some of the approaches include support vector machines, logistic regression (Muhammad et al., 2019) and artificial neural networks (Elhadad et al., 2019). The limitations of these works include low performance or unsuitability for large datasets during training and testing, inability to solve non-linear problems and high processing time. Therefore, this research developed a long- and short-term memory-based model for fake news detection. The approach was chosen because it can solve complex sequential data, is better at handling long-term dependency and is not affected by vanishing gradient problems.

Liu and Wu (2018) presented a study on the early detection of fake news on social media; RNN and CNN were combined for the detection model for better performance accuracy. The study presented an accuracy of 0.863 on the Twitter dataset; with this accuracy, it outperformed other machine learning algorithms compared with SVM, GRU,RBF and DTC. Argawal et al. (2019) worked on classifying fake news, for which many traditional machine learning algorithms were used. Naïve Bayes, Logistic Regression, Linear SVM, Stochastic Gradient Classifier and Random Forest Classifiers were used for the classification. LIAR dataset was used to train the model. The study showed that SVM and LR outperformed other classifiers with precision and recall of 0.62,0.62, and 0.61,0.6, respectively.

Literature Review

In this segment, the researchers examined other studies that are related to the current one in content and design. Ahmed et al. (2017) combined machine learning and knowledge engineering techniques to classify fake news. In order to achieve better detection, SVM was used as the machine learning model. A total of 17946 news articles were trained, and the Results showed that 2059 were not fake while others were fake and bias-related articles. Vicario et al. (2019) employed Logistic regression as a machine learning algorithm for the classification of fake news using a big Italian dataset that comprises true and false news posted on the most used social media platform (Facebook), and a performance accuracy of 91% was achieved. Fayaz et al. (2021) conducted a study on detecting fake news using the ISOT dataset. The authors used Random Forest as the classification model benchmarked with other machine learning algorithms (extreme Gradient Boosting (XGBOOST), Gradient Boosting Machines(GBM), and Adaptive Boost Regression model).

Hansrajh et al. (2021) conducted a study for fake news detection using a blending ensemble learning approach; the authors employed ridge regression, Logistic regression, stochastic gradient descent, linear discriminant analysis and Support Vector Machine. The same ISOT and LIAR datasets were used by some authors, as presented earlier. This study achieved a very good performance accuracy of 79.9% when evaluated. Galli et al. (2022) combined both machine learning and deep learning approaches to different datasets for fake news detection. CNN used on the small PoliFact dataset gave an accuracy of 75.6%; this performance accuracy outperformed other models (Random Forest, Logistic Regression, Gradient boost, and BiLSTM) used.

Most of the literature used English word datasets to detect fake news, but Fouad et al. (2022) conducted a study using Arabic language-based news data. The authors used CNN, LSTM and BiLSTM with some traditional machine learning algorithms; the size of the dataset used was 4561, with biLSTM achieving the best performance accuracy of 75%, outperforming the other models employed. Aslam et al. (2021) conducted a study on the LIAR dataset to detect fake news; this study employed an ensemble-based deep learning approach for classifying the news as fake or real news. The study used the biLSTM-GRU model for attributes that represented a textual statement, while the deep, dense learning model was used on other attributes that were not. Ozbay and Alatas (2019) designed a two-step method to identify the "fake news on social media", which has several steps like pre-processing, vector conversion, and classification. The authors employed many supervised machine learning algorithms like decision tree, sequential minimal optimisation (SMO), J48, Attribute selected classifier (ASC), kernel logistic regression (KLR) simple cart, ordinal learning model (OLM), locally weighted learning (LWL), Ridor, bagging, multilayer perceptron (MLP), classification via clustering (CvC), logistic model tree (LMT), stochastic gradient descent (SGD), ZeroR, decision stump, OneR, JRip, have been experimented in the dataset for transforming the structured format with the text mining algorithms. Saleh et al. (2021) adopted an optimised CNN model for detecting fake news, where N-gram and TF-IDF performed the feature extraction from input data. They have used several layers for extracting low-level and high-level features. The parameters in every layer were optimised through grid search and hyperopt optimisation algorithms. The model achieved good performance accuracy when benchmarked with other machine learning algorithms.

Kumar et al. (2019) compare multiple state-of-the-art approaches like CNN, Bi-LSTM, Ensemble and attention mechanism Method for the detection of fake news using Twitter and Polifact Dataset; the result shows that CNN + Bi-LSTM, Ensemble and Attention Mechanism gave an average accuracy of 88.78%. Khanam et al. *(*2021*)* conducted an analysis research on fake news detection by employing some traditional machine learning models like XGboost, KNN, LR, SVM, NB and RF using LIAR dataset result shows that XGboost gave the highest average accuracy of 75% while SVM and RF gave an average accuracy of 73% respectively. All existing systems were trained using foreign datasets, which makes them unsuitable for use in Nigeria. Hence, this research developed fake news detection systems for Nigeria.

Methodology

This research developed a LSTM based model for the detection of fake news and the dataset used in training the fake news model was obtained from Nigerian newspapers and Kaggle. These datasets were preprocessed using some text preprocessing techniques like Stemming, lemmatisation, removal of stopwords and punctuations, label transformation, tokenisation and vectorisation. This stage was followed by the feature Extraction stage, where the word embedding feature was performed. After the datasets had been preprocessed, the extracted features were trained using LSTM and a hybridized LSTM-CNN model for fake news detection. The system was thereafter evaluated using various evaluation metrics like accuracy, Precision, Recall, F1score and AUC. The developed system was compared to other machine learning algorithms. The summary of all the phases involved in the development of this system is represented by a block diagram as shown in Figure 1.

Data Acquisition

The dataset used for the detection of fake news was obtained from various Nigerian dailies like *Tribune*, the *Nation*, *Vanguard*, *Daily Trust*, *Daily Post*, *Punch* newspaper, *Sahara Reporters*, *Premium Times*, *Guardian*, *Leadership*, The *Cable*, *Thisday* and *Daily Independent* newspapers from their online platforms. The dataset contains attributes like Uniform resource locator (Url), Title, Body and Class. A total of 100 local news data sources were acquired from these newspapers. The acquired dataset was downloaded from Kaggle and named "fake_or_real_news". The dataset comprises 7795 news, balanced with 3898 real new instances and 3897 fake news instances. The dataset obtained from Kaggle consists of attributes like title, text and label. Due to the dataset being balanced, the dataset does not need any dataset-balancing techniques.

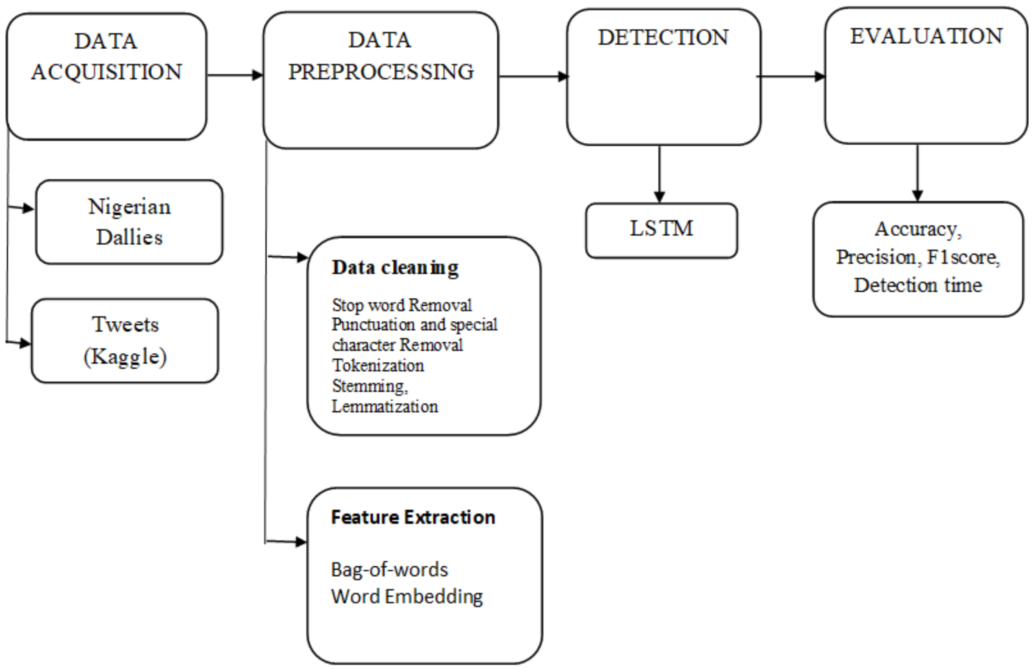

Figure 1: Block diagram of LSTM-based Fake News and Cyberbullying detection model

Design of LSTM-Based Model for Fake News Detection

The LSTM model contains three gates and one cell state; this cell state serves as a memory for the LSTM model for remembering the past; the three gates are forget gate (f), input gate(i) and output gate(o). Gate in LSTM is a sigmoid activation function which produces a value between "0 or 1"; many times, it is either "0 or 1". We use sigmoid activation function because we want the gate to produce a positive value "1". In this model, value "0" means the gate will block data from passing through the gate, while value "1" means the gate will allow data to pass through the gate. The process inside the LSTM model during the implementation of the fake news detection is mathematically expressed in equations 3.1 to 3.3.

$$i_t = \sigma\ (w_i(\ [h_t - 1, x_t] + b_i \quad \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots(3.1)$$

$$f_t = \sigma(w_f(\ [h_t - 1, x_t] + b_f \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots(3.2)$$

$$o_t = \sigma\ (w_o(\ [h_t - 1, x_t] + b_o) \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots(3.3)$$

$$c_t' = tanh(w_c(\ [h_t - 1, x_t] + b_c) \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots(3.4)$$

$$c_t = f_t c_{t-1} + i_t c_t' \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots(3.5)$$

$$h_t = o_t \tanh\ (c_t) \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots(3.6)$$

Equations 3.1, 3.2, and 3.3 represent the Equation of LSTM gates, while equations 3.4, 3.5 and 3.6 represent the LSTM Cell State (Takur, 2018). Where $i_t = Input\ Gate,$

$f_t = Forget\ Gate, o_t = Output\ Gate,$ σ = *Sigmoid function*,

$w = weight\ of\ the\ respective\ gate\ (neuron),$

$h_t - 1 = output\ of\ the\ previous\ LSTM\ block\ at\ (tims\ stamp\ t - 1)$

$x_t = input\ at\ current\ timestamp,$ b $= Bias\ for\ the\ respective\ gates$

$c_t = cell\ State\ (memory) at\ timestamp\ (t),$

$c_t' = candidate\ for\ cell\ State\ at\ timestamp\ (t)$

Implementation of the designed model for fake news detection

The other phase of the second objective of this research is to implement the design system for fake news using the LSTM algorithm with Python 3.9 programming language on Google Colab: a virtual machine for Jupyter Notebook developed by Google mainly for research purposes. The detection using a deep learning approach involves a series of steps after the needed Libraries like Pandas, Numpy, Sklearn, Tensorflow, Keras, Nltk have been imported. The following steps were followed: Reading the dataset, preprocessing the dataset, splitting the dataset into training and testing, Building the long-term term Memory (LSTM), Performing detection of fake news and cyberbullying using the developed LSTM and evaluating the system.

Import of Libraries and loading the Datasets.

At the implementation stage, once the Google Colab platform has been launched, the next step is to import all the needed libraries for the implementation of the system. Some of the imported libraries are Pandas, Numpy, Sklearn, Tensorflow, Keras, and Nltk.

Data Preprocessing

The acquired dataset was pre-processed using the following techniques: Data cleaning, Lemmatization, Stemming, Removal of stop words and Punctuation marks, Label transformation, Tokenization, Text length uniformity, Vectorization

i. Data Cleaning

In this stage, the outliers (unimportant attributes) were removed for effective usage of the dataset. Removing these attributes helped the system concentrate on only the useful ones. In this stage, the serial number and title were dropped. This left our dataset with only the text and label columns. Raw news datasets collected from Nigerian Dallies or open access data repositories for fake news detection and social media platforms for cyberbully detection news were cleaned of some noise or outliers irrelevant to the developed system.

ii. Lemmatization

WordNet Lemmatizer was employed in this research for lemmatisation due to its good performance as obtained from different literature.

iii. Stemming

With the reduction of words to their stem it gives room for the model to focus on the main words for classification and helps in accurate classification. Porter Stemmer was used for stemming in this research work.

iv. Removal of Stopwords and Punctuations

Stopwords words are words in any language that do not add meaning to a sentence and removal of these words will help in the drastic reduction of data size and system's performance accuracy. Mostly when working with natural language processing, punctuation marks, special characters, and emoji usually don't have relevance with the nature of the news nor the content of bully words, so these marks and symbols are mostly discarded to reduce the size of data and increase computational time.

V. Label Transformation

The dataset's labels are in the form of categorical data type (fake and real), this type of data type cannot be inputted into the model for processing. Therefore, there is a need to transform these labels into their corresponding binary equivalent. Label encoding and one-hot encoding are the most common type of encoding techniques used by various researchers. However, manual encoding are also used for the correct encoding, this is the approach used for assigning this categorical labels to their relevant binary values (0 and 1).

vi. Tokenization

This is the process of breaking a textual dataset into smaller pieces like words, sentences, terms and any other syllabic elements, these smaller pieces are known as Tokens. This is sometimes the first stage in natural language processing techniques. Tokenizer breaks stream of unstructured textual data into discretized elements. Tokenizer was imported differently from the text preprocessing library.

vii. Vectorization

This is the process of converting text into vectors as models will not understand text as input. In order to achieve this, one hot representation was used.

Feature Extraction

It is an approach for representing words and documents. Word Embedding or Word Vector is a numeric vector input that represents a word in a lower-dimensional space. It allows words with similar meanings to have a similar representation and can also approximate meaning. This research used a word vector feature of 300, this is to give room for wider capturing of unique features.

Data Balancing

The locally acquired dataset is highly imbalanced and when implemented only real news was detected leaving fake news undetected. As a result of this, there arises the need to balance the two classes so as to ensure even detection. Since the local dataset is not that large, the best approach for balancing it is oversampling, which involves increasing the minority class to the same number as the majority class. In order to achieve this, Synthetic Minority Over-Sampling Techniques (SMOTE) were employed.

Dataset Splitting

The dataset for this model was divided into training and testing, 80% for training, and 20% for testing, the reason for 80% for training was to enable us to have enough data for training our model.

Training the LSTM Model for fake news and cyberbully detection

In training the long short-term memory (LSTM) model, 80% of the dataset was used for training while the remaining 20% was used for testing. The LSTM recurrent unit tries to remember all the past knowledge that the network has seen so far and to forget the irrelevant data, this is done by introducing a different activation function called gate and also has an internal sector called cell state.

Testing the data

Twenty per cent (20%) of the dataset is hereby put into test after the training exercise is completed; all these are done inside the SkLearn python library. It was after the result had been tested that the developed LSTM model detected whether news is fake or real and whether a tweet or post is online bullying or not.

Methods for Evaluation of the Developed Model

Four different metrics, i.e. accuracy, precision, recall and F1-measures, were used to evaluate the performance of this model. The confusion matrix provides the details of the following values: True Positives (TP), True Negatives (TN), False Positives (FP) and False Negatives (FN).

Result and Discussion

Determination of Optimal Feature and Parameter

The news dataset comprises of different attributes like the date of the news or tweet, URL of the news or tweet, author/ handle of the news or tweet, title of the news, text, article or tweet and class label. These selected attributes are the optimal attributes considered by most researchers for developing such a system. Due to the hybridization of CNN and LSTM, the parameters are determined using the varying input layer units. The input units' values are to the power of 2, in order to have the optimal parameter, 128 input units are used for both CNN and LSTM as this gave the best performance accuracy for the developed system. The 128 units for CNN and LSTM gave a total trainable parameter of 1,823,841. Due to our diverse dataset, the performance accuracy obtained from hybridized CNN-LSTM and ordinary LSTM varies. CNN-LSTM gave the best performance with the Kaggle dataset at 128-8 hidden layers, while LSTM with the same number of hidden layers with the epoch of 150 and batch size of 64 gave the best performance, LSTM with the same parameters and training arguments gave the best performance accuracy.

Evaluation Result of the developed Fake News Detection System

Hybridized CNN-LSTM system used input units of 128 each. The system used two different fake news datasets; Kaggle dataset and the locally acquired dataset from Nigerian Dallies. The results gotten from these datasets are presented in the Table 4.1 that follows. The kaggle dataset for fake news detection comprises of author, title, text and label out of which only text and label were used for the development of the system. The optimal parameter used was CNN 128 input units and 128 LSTM input units. This amounted to a total of 1, 823,841 total and trainable parameters.

The developed system was trained with 100 epochs and 64 batch sizes with validation spilt of 0,2, the system gave an accuracy of 83.5% with a weighted average for precision, recall and F1score are 84% respectively and detection time was 2.56secs. Table 4.1 shows the evaluation result of the fake news detection using the kaggle and Nigerian news datasets.

Table 4.1: Performance Evaluation of the developed Fake news system using Kaggle Datasets

S/N	**Dataset**	**Algorithm**	**Avg. Accuracy (%)**	**Avg. Precision (%)**	**Avg. F1Score (%)**	**Detection Time (Sec)**
1	Kaggle Dataset	CNN-LSTM	83.50	84	84	2.56
2	Balanced Nigerian News Dataset	LSTM	92.86	94	93	0.417

Comparison of the developed fake news detection system with other Machine Learning Algorithms.

The developed system was compared with other machine learning algorithms like Support Vector Machine (SVM), K-Nearest Neighbor (KNN) and LSTM. The detection of fake news using the CNN-LSTM using Kaggle dataset gave the best performance accuracy compared to other machine learning algorithms, while LSTM gave the best performance when the local news dataset and cyberbullying dataset were used. Table 4.2 shows the performance evaluation of the developed system and another machine, as mentioned above, learning algorithms.

Table 4.2: **Comparison of the developed Fake News Detection System with other ML algorithms using Kaggle Dataset**

S/N	**Algorithm**	**Avg. Accuracy (%)**	**Avg. Precision (%)**	**Avg. Recall (%)**	**Avg. F1Score (%)**	**Detection Time**
1	CNN-LSTM	83.50	84.00	84.00	84.00	2.36
2	LSTM	82.00	82.00	82.00	82.00	3.06
3	KNN k=3	66.14	79.00	66.00	62.00	1.37
4	SVM	60.00	60.00	60.00	60.00	2.44

As represented in Table 4.2, the best performing algorithm for fake news detection using the Kaggle Dataset for fake news names “fake-or-real-news” was the hybridised CNN-LSTM, which gave an accuracy of 83.50%, followed by LSTM, which gave an accuracy of 82%. However, regarding the prediction time, the fastest model for detecting fake news with the Kaggle dataset is the K Nearest Neighbor, which gave a detection time of 1.37 seconds.

The Nigeria news dataset obtained from various Nigerian dallies was experimented with in its imbalanced form with various traditional machine learning and deep learning approaches. The experimental results are presented in Table 4.3 with their various evaluation metrics and fake-real news detection time.

Table 4.3: Comparison of the developed Fake News Detection System with other ML algorithms using Imbalanced Nigerian News Dataset

S/N	Algorithm	Avg. Accuracy (%)	Avg. Precision (%)	Avg. Recall (%)	Avg. F1Score (%)	Detection Time
1	LSTM	87.50	77.00	88.00	82.00	1.42
2	CNN-LSTM	81.25	76.00	81.00	78.00	0.59
3	Logistic Regression	62.50	73.00	62.00	67.00	0.60
4	KNN k=3	68.75	74.00	69.00	71.00	0.42
5	SVM	81.25	76.00	81.00	78.00	0.022

The result represented in Table 4.3 is the experimental results obtained from using the imbalanced dataset; it can be seen from Table 4.3 that LSTM gave the highest accuracy of 87.50% while SVM gave the fastest detection time of 0.022 seconds. However, from the classification results, the fake news class was not predicted at all as it was the minority class. As a result, such a dataset cannot be used since it is only one class that was detected; this was what gave reason for balancing the dataset in order to have an equal distribution of the two classes. The result obtained from a balanced dataset is given in Table 4.4.

Table 4.4: Comparison of the developed Fake News Detection System with other ML algorithms using Balanced (SMOTE) Nigerian News Dataset

S/N	Algorithm	Avg. Accuracy (%)	Avg. Precision (%)	Avg. Recall (%)	Avg. F1Score (%)	Detection Time
1	LSTM	92.86	94.00	93.00	93.00	0.42
2	CNN-LSTM	78.57	79.00	79.00	79.00	0.90

3	KNN k=3	60.71	78.00	61.00	54.00	0.40
4	SVM	82.14	87.00	82.00	82.00	0.37

The locally sourced Nigeria news data was balanced using SMOTE to ensure that both real and fake news are equally represented. As shown in Table 4.4, LSTM gave the best detection accuracy when locally sourced news from the Nigerian news dataset was used. The LSTM model gave an accuracy of 92.86%, though this local dataset was balanced using SMOTE, as when the imbalanced dataset was used, LSTM gave a performance accuracy of 87.5%, as shown in Table 4.3, though only the real news was detected. This showed that the system gave a higher accuracy with a balanced dataset. SVM also gave a better accuracy compared to the other Machine Learning algorithms. It even outperformed CNN-LSTM, which gave 78.57% performance accuracy. However, SVM gave the faster detection time of 0.37 seconds, followed by K Nearest Neighbor (k=3) of 0.40 seconds and LSTM of 0.42 seconds.
Comparing Tables 4.3 and 4.4, it was noticed that the balanced dataset gave the best performance accuracy with the various machine learning algorithms compared with LSTM giving the highest accuracy of 92.86%. However, SVM with an imbalanced dataset gave a faster detection time than a balanced dataset, which is understandable as only one class was detected with the imbalanced dataset, so a faster detection time is expected.

Comparison of the Developed Systems for Fakes News Detection Systems with the Existing Systems

The developed system using the balanced dataset was compared with other existing systems to detect fake news. The developed system gave a better performance accuracy than all the existing systems. A study by Aslam et al. (2021) was the only system that gave a performance accuracy closer to the developed systems. Table 4.8 shows the comparison result obtained when the developed system was compared with other existing fake news detection systems.

Table 4.8: Comparison of the Developed System Using Nigeria News Dataset with Existing Systems for Fake News Detection.

S/N	Author	Algorithm	System	Accuracy (%)
1	Aslam et al. (2021)	BiLSTM-GRU	Fake News	89.89
2	Balpande et al. (2021)	Naïve Bayes	Fake News	85.00
3	Galli et al. (2022)	CNN	Fake News	75.60
4	Developed system	LSTM	Fake News	92.86

Conclusion

This research developed a Fake News detection system using the Long Short Term Memory Model. The dataset used in training the model for fake news detection was acquired from Nigerian daily newspapers ranging from 2017 to 2023 and Kaggle. The Nigerian news dataset was unbalanced because there is no approved site for fake Nigerian news data. The developed systems were implemented on Google Colab with Python 3.9. the LSTM model used on Nigeria news datasets has 128 neurons at the input layer and one hidden layer with 64 neurons with *Tanh* as the activation function at the input and hidden layers, while Sigmoid was used as the activation function at the dense layer, the same design and hyper-parameters were used for the system design of CNN-LSTM. The acquired news dataset from Nigerian dallies was imbalanced, with fake news being the minority class; this dataset was used to develop a fake news detection system and compared it with some traditional machine learning algorithms. Results show that LSTM outperformed hybridised CNN-LSTM and some traditional machine learning employed with an average accuracy of 87.50%. Afterwards, the dataset was balanced using Synthetic Minority Oversampling Techniques (SMOTE), and results show that LSTM outperformed CNN-LSTM and some traditional machine learning models employed with an average accuracy of 92% for detecting fake news. This shows that a balanced dataset gives a higher performance accuracy than an imbalanced dataset. Apart from that, the imbalance dataset might not accurately detect the minority class. According to the result obtained from the training, it was found that Long Short-Term Memory (LSTM) gave us the highest detection average accuracy on a balanced Nigerian news dataset. The above result shows that the Long Short-Term Memory (LSTM) model is the best detection algorithm for fake news detection using the Nigerian news dataset. The developed system will be very helpful in detecting fake news on the Internet, drastically reducing the speed at which rumours and false news spread. This research contributed to knowledge by developing a Nigerian Fake news detection system using Long Short Term Memory (LSTM) and creating a Nigerian news dataset for fake news detection.

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